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Forecasting Stock Prices: Exploring the Potential of ARIMA Model for Short-Term Predictions

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ABSTRACT

Predicting stock prices is a difficult and mysterious task that necessitates substantial effort considering the stock market's unpredictable and uncertain nature. The valuation of stocks is extremely important in the fields of business, economics, and finance, encouraging scholars to investigate the development of effective forecasting models. Given the uncontrollable behavior of stock market investment performance, the short-term picture remains vulnerable to unforeseen difficulties, a reality that is difficult to accept. The aim of the given study is to understand how ARIMA model can help investors and financial managers make informed decisions regarding Meta Stocks. Now a day's investors are interested in putting their money into the fields which are emerging like tech-based businesses. In this paper we have used the historic data of Meta stocks to predict its future movement in the short run. Academics use scientific approaches to forecast stock values, providing vital tools for investors seeking profit accumulation and expansion. One of the models which have gained popularity in the arena of time series prediction analysis was an autoregressive integrated moving average (ARIMA). In this given study authors want to expound impact of the ARIMA model on building a better stocks price prediction. The authors of the study systematically formulated a prediction model by using timeseries data of Meta Platform Inc. stocks closing prices. We concluded that Meta Inc. data ARIMA model AR (4), AR (20), AR (30), AR (31), MA (4), MA (20), MA. (30), MA. (31) is white noise, it fits the data. The recent ending price of capital stock of Meta Platforms Inc. depends on the previous shocks of 4, 20, 30 and 31 days and the usual unpredictability of the recent price of stock was contingent on the instability in prior 4, 20, 30, and 31 days. The findings express the ARIMA model's ability to address conventional stocks price foretelling techniques, highlighting significant potential for Meta Stocks in terms of near-future forecasting given its severe volatility. This study can be especially helpful for trading near-term planning or changing long-term budgetary conditions in anticipated markets.

INTRODUCTION

Stock market is a platform where a number of buyers or investors and sellers of stock meet and exchange their values (Dhingra et al., 2024). Stock market is very unpredictable but due to huge stakes of the investors as well as the economic prosperity it is unavoidable to take risk of highly uncertain market. Forecasting techniques are very useful because through forecasting techniques we can tackle this problem and we are able to gauge the associated risk with volatile stocks and take corrective actions for future (Ali Nasser Aldine, 2023). Sustainability of businesses depends on their profitability, involvement of technology, economic prosperity and their stock prices continuous developments in this given study we were focused on how to predict stock prices movement in short time period. We have different foreseeing techniques to envisage the forthcoming moment of capital stock price, in the given study our focus is how accurately ARIMA model help to predict the future movement of Meta stocks. Projecting is a process of identifying or guessing about the future value of any given variable (Dabas & Nagvanshi, 2024). If we want to predict and investigate about the future value of variables some forecasting methods like which includes Auto regressive (AR), means dependent variable has is lag as independent variable Moving Average (MA) which means dependent variable depends on its error term, combination of ARMA and ARIMA model, some other forecasting techniques also includes, Neural network (NN) and Croston are very helpful (Zhang et al., 2024). Capital stocks markets have a valuable role in an financial development for each country (Ali et al., 2022; Shomaila Habib, Mehtab Habib, 2024), currently US stock market capitalization having the worth of *$46,199,811.4 million* (*U.S. Stock Market Total Market Value | Siblis Research*) so, a lot of current as well as potential investors who were interested to know how much the stock market volatile take the risk accordingly. Investors interested to know about the associated risk with their investment as well as another reason was the wealth maximization (Smith, 2024), it is a crucial task for the finance managers of any organization to predict and maintain the stock price in the market because it significantly impacted on the decision making process of investors (Horne & John M. Wachowicz, 2018). Stock market was highly volatile and it involves a lot of risk in terms of dropping the value of stock (shear & Ashraf, 2022; Shomaila Habib, Mehtab Habib, 2024). There are different types of investors on the basis of risk undertaking, some investors were highly aggressive like they prefer to take the risk some investors did not want to take risk and considered to risk averse some investors show the nature of risk indifferent (Horne & John M. Wachowicz, 2018). Investors who take the decision to finance in the securities market having the nature of taking risk so, due the volatility in stock prices, prediction about the future stock price will helpful for all those investors who were risk takers and aggressive in their decision making (Luo et al., 2023).

Stock price prediction is a challenging task in the business sector, and scholars have directed several studies to forecast the direction of stock market indexes (Ali Nasser Aldine, 2023; Barajas et al., 2023; Minhaj et al., 2022; Rodoni et al., 2022). Researchers found numerous factors such as political situation, economic situation, and traders' anticipations can influence stock market indexes (Qiu & Song, 2016a). To foretell the trend of securities market indexes, investigators have used different input variables and models.

Previous studies (Bakoush et al., 2020; Paul et al., 2023; Perraudin, 2014; Habib et al., 2024) show that investing in the stock market are highly volatile and risky compared to the other investment opportunities like investment in fixed deposit, investing in gold, and investment in real estate. Different econometrics models were very helpful in overcoming the problem of risk involvement due to the uncertain situation of the stock market (Minhaj et al., 2022). Econometrics models were very useful because they can forecast the assets or securities' appreciation or depreciation value furthermore models were also very helpful for understanding the current situation as well as the future prediction about the security prices and are used for the transparent analysis of the situation (Manigandan et al., 2023; Raza & Iqbal, 2023). The process that guides model selection in econometrics is heavily influenced by the type of data being examined. Logit model - e.g., used for estimating the probability of an event, given one or more independent variables; commonly implemented in finance and marketing applications as well as many social science fields where binary outcome data are analyzed. The autoregressive (AR) model is a widely used time series analysis technique that involves regressing the variable on its lagged values, making it exceptionally useful when applied to forecast variables such as an economic indicator or financial data. The moving average (MA) model, in contrast, tends to smooth the time series data through averaging past values assisting with noise reduction and trend analysis.

The autoregressive moving average (ARMA) model combines the AR and MA components to build models for stationary time-series data which reflects both autoregression as well as a general trend. For data that is non-stationary, the autoregressive integrated moving average (ARIMA) model takes this a step further incorporating differencing and making it also useful for forecasting but also economic modeling. The ARCH Estimation solves another issue: time-varying volatility which is especially an important feature in financial markets due to the prevalence of Volatility clustering. Extending the ARCH model, with this feature Generalized Autoregressive Conditional Heteroskedasticity (GARCH) integrates both short- and long-term variation effects for better forecasting of volatility. It followed by the Vector Autoregressive (VAR) model for multivariate time series, capturing the interdependencies across several variables and commonly used in macroeconomic modeling. They have different applications, strengths, and weaknesses. Each of these models is meant for specific types of econometric analyses and data (Minhaj et al., 2022).

The outcome of ARIMA model used to assess the strength of the dependent variable when compared with different fluctuating independent variables. By excluding systematic and seasonal variability from the data set, this model focused on differences between the series values of the data set rather than the actual values of the data set. The ARIMA model can also be useful to foresee future movement of the securities or stock market in the short run (Minhaj et al., 2022). Different studies (Lahmiri & Bekiros, 2020; Travis-Lumer et al., 2023; Yun & Moon, 2014) show if we want to predict the future value of time series data it will depend on the recent, previous, and white noise values of the time series data. ARIMA model foundation is based on the fact that the past values of any dataset series will have some relationship with the future and the present value of that dataset series so, as a stakeholder, forecasting through the ARIMA model in the short run, can help the user to know about

the current and future fluctuations in their selected security (Tihi, 2023). Many researchers used the ARIMA model for forecasting, evaluation and consistency of time series statistics to evaluate and forecast the future movement (Ahmar & del Val, 2020; Minhaj et al., 2022; Tihi, 2023). ARIMA model was used in different sectors like environment forecasting, sales forecasting and future demand forecasting (Kaur et al., 2023; Ullah & Haider, 2010) it can also use to predict about the environmental changes, (Chodakowska et al., 2023) applied ARIMA model for understanding about the forecasting of solar radiation, (Barajas et al., 2023) also used ARIMA model for detecting the ground water pollution. Based on previous said studies, we were use the ARIMA model to forecast about the Meta platforms, Incorporation stock. These days, many investors are looking at the social media industry and are interesting in buying stocks of different social media platforms (Dabas & Nagvanshi, 2024) .

The ARIMA model has greatly been employed in stock price prediction and has offered remarkable results in short term forecasting (Khan & Gunwant, 2024) . It has been compared to other models like artificial neural networks and non-parametric machine learning models. The selection of input variables and optimization techniques for the model can also affect how accurate stock prices predictions are made.

The objective of the given study was to investigate how well the ARIMA model predicts stock prices, especially Meta Platforms Inc. Because these insights can be used by managers and investors to help make better investment choices. Financial managers can optimize investments and reduce exposure to risk by understanding how past market shocks have affected current pricing and strategies for anticipating future growth. Using this information, managers can more accurately forecast and prepare for potential market fluctuations, enabling them to implement more successful risk mitigation strategies.

LITERATURE REVIEW

Due to increasing globalization and technological advancements, the spread of information in stock markets from many variables has increased. The stock market has a system that enables the purchasing and exchange of shares in publicly traded corporations (Dhingra et al., 2024; Shoaib Ali et al., 2024). The supply of shares from existing investors looking to sell or the demand for shares from new investors looking to buy determines how much a stock is worth (Castro & Jiménez-Rodríguez, 2024a, 2024b). An investor's decision to purchase or sell is shaped by numerous factors containing company performance, state of the economy, share price at that time, among others (Islam & Rony, 2024). There are several reasons as to why people buy stocks: Some people hold onto their shares with the aim of earning dividends. Some may take it as gambling upon a stock, wanting to buy low and sell high later because they believe it will rise. Others could be interested in having some control over how certain companies are run. In stock price prediction the ARIMA model has been used extensively (Ma et al., 2023). Also, several (Ahmar & del Val, 2020; Chodakowska et al., 2023; Minhaj et al., 2022; Saxena & Singh, 2022) have found that there are significant results of using an ARIMA model for short term prediction. For example, one study used the ARIMA model to predict volatility in Indonesian stock prices and found that it was credible, easy to use and broadly used for forecasting

stock price volatility (Kaur et al., 2023; Saxena & Singh, 2022) used the ARIMA model to predict environmental changes, (Chodakowska et al., 2023) utilized the ARIMA model for understanding solar radiation forecasting while (Barajas et al., 2023) also used ARIMA model to detect ground water pollution. . Another study confirmed the promise of the ARIMA model in this domain by examining short-term stock market forecasts on the Nigerian Stock Exchange and the New York Stock Exchange (Ma et al., 2023).

Chun et al., (2023), had explained the international drivers for stock market volatility in their paper, the results of the mentioned study concluded that Chinese securities market had a substantial impact on US stocks market movement, in another study in which researchers compared two different investment variables to predict the performance of Japanese capital markets. The study used an augmented (artificial neural network) ANN model and determined The ability of hybrid genetic algorithms to predict stock price movements (GA)-ANN model The results exhibited that type (II) input variables lead to high prediction accuracy and augmented (artificial neural network) ANN model can be enhanced by appropriate selection of input variables (Qiu & Song, 2016b).

Pyo et al., (2017), focused extensively on the use of non-parametric machine learning models to forecast the dynamics of the Korea Composite Stock Price Index 200 (KOSPI 200). Artificial neural networks and support vector machines with polynomial radial basis function kernels were used in the analysis. However, the finding of study was inconsistent with previous research, and the collective methods did not better the precision of the projection (Pyo et al., 2017).

Furthermore, the ARIMA model has been used to examine the effectiveness of flexible Shariah capital markets in ASEAN countries (Rodoni et al., 2022) According to the results of a study, the ARIMA model can be used to predict the stock price of Indonesia Sharia Stock Index with an accuracy of 78% (ISSI). However, it was determined that the ISSI index was ineffective based on the test of paired sample t-test (Rodoni et al., 2022). Different studies prefer ARIMA model for the prediction using time series data (Ahmar & del Val, 2020; Ali Nasser Aldine, 2023; Minhaj et al., 2022; Rodoni et al., 2022).

The study which used the ARIMA model for the prediction of JNJ's future stock price and fluctuation of selected stock market concluded that the ARIMA model was effective to use to predict in a shorter run (Minhaj et al., 2022). Another study (Luo et al., 2023) which used managerial compensation variables, operational efficiency, and corporate risk using data from companies listed in Taiwan on Taiwanese stock exchanges. Using the ARIMA model to forecast the risk involved paints a clear picture.

In one of the empirical research studies, which was based on Lebanese stocks exchange, also used the ARIMA model to prepare the best model for the sake of forecasting about the stock price of banking firms finding of the study demonstration that the Lebanese stock market can be predicted through the ARIMA model (Ali Nasser Aldine, 2023).

In time series forecasting research, autoregressive integrated moving average (ARIMA) models play an important role in temporal data analysis and forecasting received considerable attention due to their effectiveness in capturing and forecasting temporal patterns in data This paper investigates in detail the stock price forecasting platform it goes deeper into doing it. The ARIMA model is particularly suited to this task because it combines three main features: autoregression (AR), which models the relationship between a model and a number of followed distinct models (I), which gives the mean of the time series depending by the eliminating quality is times of use; and the moving average (MA), which captures the relationship between the observations and the residual errors from the moving average model. By combining these features, the ARIMA model can efficiently analyze and forecast currency price movements, accommodating a variety of complex challenges in economic time series data.

The platform designed to provide intuitive visualization tools, allowing users to quickly interpret forecasts and inform investment decisions. Through detailed case studies and empirical results, the paper demonstrates the application of the ARIMA-based platform in real-world stock market situations. It uses a comprehensive approach to policy adoption to fulfill stock price forecasts, this research offers invaluable insights and tools for students and practitioners.

RESEARCH METHODOLOGY

In this study, we have taken epistemological research assumptions and use the research philosophy of positivism, because we have quantitative time series data of Meta platform Inc. stocks. In this study author used the deductive approach because the deductive research method looks at an established theory or practice and evaluates its application to a given set of circumstances., and the action research strategy opted for the given study because Action research bases pedagogical decisions on real-world experiences, bridging the gap between theory and practice. The methodological choice behind the given study was quantitative because in this study authors used the Meta Inc time series data. Dataset used in the given study based on time series daily data of Meta stock, closing prices, ranges from July 19, 2021, to July 18, 2023, having total observation of 503 used in this study. The source of the data was Yahoo Finance. Historical data which were collected from the given source have five different components open, high, low, Adj Close, and closing stock price. In this study we used the closing price of stock because it reflects the entire day movement in the stock price in any trading day. For analysis of data E-views twelve used in this study.

Different studies prefer ARIMA model for the prediction using time series data (Ahmar & del Val, 2020; Ali Nasser Aldine, 2023; Minhaj et al., 2022; Rodoni et al., 2022).

Following was the general equation for short term prediction of Meta stocks.

$$P_t = c + \beta_1 P_{t-1} + \beta_2 P_{t-2} + \beta_3 P_{t-3 \dots\dots\dots\dots} + \beta_n P_{t-n} + +\gamma_1 E_{t-1} + \gamma_2 E_{t-2} + \gamma_3 E_{t-3 \dots\dots} + \gamma_n E_{(t-n)} + \varepsilon$$

Based on previous studies we also use ARIMA Model in this study. The ARIMA Model has different five stages which were presented by Box Jenkins in 1970, phases of the ARIMA pattern as follows.

Stage 1: In the first step, we checked the stability of the data, including examining statistical features such as mean, variance, covariance, and standard deviation If these characteristics remain constant at in time and does not depend on time, then a time series considered stable. It is important to ensure the accuracy of the information to obtain reliable prediction results. This phase, known as the identification phase, is important because if the data is unstable, the predictive model may not perform well. Checking stability is therefore an important first step.

The basic rules for choosing an appropriate model are as follows: If the time series data are stable in level, the ARMA model should be used; If the data are not stable in level but stable when differentiated, the ARIMA model is more appropriate. Figure 1 shows that the time series data were unstable at the level but stable after applying the first difference. As a result, we used the ARIMA model for forecasting.

Stage 2: In this step, we convert the non-stationary data to static forms by using the first difference. The results shown in Figure 2 show that the time series data for the meta stock remained stable after these changes. After contrasting the data, we extracted trends and kept statistical factors, such as mean and variance, stable over time, thus satisfying the requirements for improved prediction using the ARIMA model.

Stage 3: In this step, we used a combination of autoregressive (AR) and moving average (MA) models to determine the most appropriate ARIMA models for predicting future trends in meta-stocks pricing, and autocorrelation functions (ACF) and partial also autocorrelation functions (PACF). the analysis of the. Table 1 presents the results of the tested models, showing their performance and helping to select the best ARIMA algorithm for accurate forecasting.

Stage 4: After a thorough examination of Table 1, we were able to develop our ARIMA model based on the optimal values of the autoregressive (AR(p)) component, integration (q), and moving average (MA) components The most appropriate combination of (p), (d), and MA(q)-parameters can be selected.

Stage 5: In the prediction step, we compare the predicted values generated by our ARIMA model with the actual observed values to evaluate the accuracy and efficiency of the model by predicting the future price of a meta-stock closing prices are better predicted against actual data. By analyzing the difference between the predicted and actual values, we can assess the performance of the model and make any necessary adjustments to improve the accuracy of the predictions.

RESULT AND DISCUSSION

Figure 1 presents a line graph of daily time series data for Meta stock, covering the period from July 19, 2021, to July 18, 2023. This data set contains 503 observations, each trading day represented Closing meta stock price. The graph clearly shows the rapid volatility of Meta's stock price over this period. The reference image reveals the unstable behavior of the stock, as reflected in the random walk pattern seen in the line graph. This random walk means that average stock prices and volatility are not constant over time, which is a typical characteristic of volatile data.

The variability in the raw data indicates that Meta prices influenced by many factors, such as market sentiment, economic dynamics, sector-specific events and the lack of a fixed average or constant volatility highlights the challenge of predicting future share prices based solely on history. The random step behavior observed here is characteristic of many economic periods in a row, where past price movements do not provide a reliable basis for predicting future prices.

These variations and inconsistencies in data require the use of sophisticated forecasting models such as ARIMA, which can account for these variables and help achieve more accurate forecasts Understanding these variables is important for investors and analysts to explore such time series data of interest models Practices should also be carefully considered, as they play an important role in how accurately and reliably any forecasting model used in the stock market.

Figure 1. Data Source: Yahoo Finance, closing Stock prices of Meta Platform Inc

Date: 07/19/23 Time: 12:03
Sample: 7/19/2021 7/18/2023
Included observations: 503

Lag	AC	PAC	Q-Stat	Prob
1	0.993	0.993	499.34	0.000
2	0.987	-0.003	993.05	0.000
3	0.980	-0.028	1480.8	0.000
4	0.973	-0.005	1962.7	0.000
5	0.966	0.013	2438.9	0.000
6	0.960	0.012	2909.6	0.000
7	0.954	0.028	3375.2	0.000
8	0.947	-0.028	3835.6	0.000
9	0.941	0.050	4291.3	0.000
10	0.935	-0.030	4742.1	0.000
11	0.929	0.002	5187.9	0.000
12	0.923	-0.035	5628.5	0.000
13	0.916	-0.039	6063.4	0.000
14	0.909	-0.026	6492.4	0.000
15	0.901	-0.017	6915.1	0.000
16	0.894	0.025	7332.1	0.000
17	0.887	-0.002	7743.4	0.000
18	0.880	-0.023	8148.9	0.000
19	0.873	0.009	8548.7	0.000
20	0.866	-0.009	8942.9	0.000
21	0.858	-0.058	9330.9	0.000
22	0.850	-0.011	9712.5	0.000
23	0.843	0.019	10088.	0.000
24	0.835	0.028	10458.	0.000
25	0.828	-0.045	10822.	0.000
26	0.820	-0.004	11180.	0.000
27	0.812	-0.042	11531.	0.000
28	0.803	-0.004	11877.	0.000
29	0.795	0.024	12216.	0.000
30	0.787	-0.024	12549.	0.000
31	0.780	0.042	12876.	0.000
32	0.772	-0.065	13197.	0.000
33	0.763	-0.000	13512.	0.000
34	0.755	-0.003	13820.	0.000
35	0.747	0.011	14123.	0.000
36	0.739	-0.028	14420.	0.000

Figure 2. Correlogram of Meta Platform Inc. closing stocks prices at level

Figure 2 Meta Platforms Inc. The autocorrelation function (ACF) plot indicates that the ACF is not flat and shows significant values that extend beyond acceptable confidence limits This chart indicates that the data exhibit strong serial correlation, which is when instability characteristic sequence.

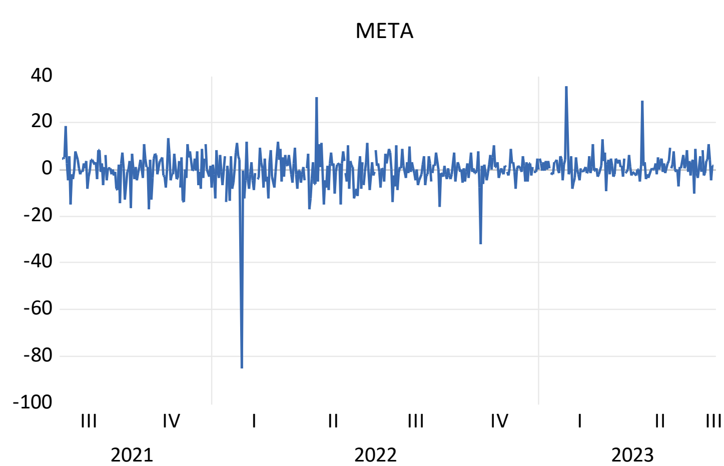

Figure 3. Line graph of Meta Platform Inc. closing stock prices at first difference

Above Figure 3, shows a stable behavior in time series data for closing stock prices of Meta Platforms, Inc. The mean and standard deviation remain stable after the first intercept, indicating that the data no longer show a random walk this has made the time series stable This has been confirmed.

Date: 07/19/23 Time: 11:59
Sample (adjusted): 7/20/2021 7/18/2023
Included observations: 502 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.016	-0.016	0.1343	0.714
		2	0.029	0.028	0.5498	0.760
		3	-0.032	-0.032	1.0847	0.781
		4	-0.092	-0.094	5.4012	0.249
		5	-0.002	-0.003	5.4030	0.369
		6	-0.022	-0.018	5.6473	0.464
		7	0.030	0.024	6.1110	0.527
		8	-0.035	-0.043	6.7539	0.563
		9	0.050	0.046	8.0242	0.532
		10	0.034	0.036	8.6226	0.568
		11	0.056	0.058	10.244	0.509
		12	0.049	0.046	11.496	0.487
		13	0.011	0.022	11.557	0.564
		14	0.023	0.030	11.823	0.621
		15	-0.021	-0.003	12.059	0.675
		16	-0.028	-0.023	12.454	0.712
		17	0.036	0.044	13.113	0.729
		18	-0.023	-0.018	13.400	0.767
		19	-0.006	-0.015	13.419	0.816
		20	0.085	0.082	17.251	0.637
		21	0.045	0.047	18.303	0.630
		22	0.001	-0.012	18.304	0.688
		23	-0.036	-0.044	18.994	0.702
		24	0.052	0.063	20.443	0.671
		25	-0.002	0.014	20.446	0.723
		26	0.058	0.051	22.256	0.675
		27	-0.008	-0.012	22.292	0.722
		28	-0.061	-0.051	24.253	0.668
		29	0.000	-0.001	24.253	0.716
		30	-0.121	-0.117	32.076	0.364
		31	0.118	0.094	39.547	0.140
		32	-0.003	-0.006	39.552	0.168
		33	0.048	0.026	40.809	0.165
		34	-0.035	-0.059	41.474	0.177
		35	0.035	0.051	42.154	0.189
		36	0.016	0.013	42.288	0.218

Figure 4. Correlogram of Meta Platform Inc. closing stock prices after the first difference

For the confirmation of stationary of data again applied the Correlogram test and the values of ACF and PACF are flatter in above Figure 4 which also confirms the stationary behavior of time series data at first difference. Some values show significant behavior in the above Correlogram which was used to build the ARIMA model for forecasting purposes. For further verification of data stationarity another test was also applied which is called the augmented Dickey-Fuller unit root test, it also verifies that the time series data of Meta stocks becomes stationary after the first difference because it has a probability value less than 0.05 see in Figure 5.

Null Hypothesis: D(CLOSE) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=17)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-22.71459	0.0000
Test critical values:	1% level	-3.443175	
	5% level	-2.867089	
	10% level	-2.569787	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CLOSE,2)
Method: Least Squares
Date: 07/19/23 Time: 11:57
Sample (adjusted): 7/21/2021 7/18/2023
Included observations: 501 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CLOSE(-1))	-1.016312	0.044743	-22.71459	0.0000
C	-0.059959	0.323748	-0.185203	0.8531

R-squared	0.508351	Mean dependent var	-0.006547
Adjusted R-squared	0.507366	S.D. dependent var	10.32411
S.E. of regression	7.246273	Akaike info criterion	6.802836
Sum squared resid	26201.72	Schwarz criterion	6.819668
Log likelihood	-1702.110	Hannan-Quinn criter.	6.809440
F-statistic	515.9527	Durbin-Watson stat	1.999853
Prob(F-statistic)	0.000000		

Figure 5. ADF unit root test for Meta Platform Inc. closing stock prices after first difference.

In below table 1 we have analyzed different ARIMA models based on significant values of ACF and PACF which were also determined in Figure 4. AR (4), AR (20), AR (30), AR (31), MA (4), MA (20), MA (30), and MA (31) represent the significant values and because of different combinations of these significant values a new forecasting ARIMA model was developed in this given study. We have taken five parameters to find the best-fit model. Our first parameter was AIC (Akaike Information criteria) lowest value of AIC best suited the for good ARIMA Model. Our second parameter was the adjusted R square, the highest adjusted R square best suits the good ARIMA Model. Our third parameter was using significant coefficient values, for the best ARIMA model the highest considerable number coefficient was used. Our fourth parameter for the ARIMA model was the sigma square value, the rule for selecting the best model was lowest sigma square value was preferred. Based on Table 1 best ARIMA model that we have predicted for the Meta stocks is the AR(4), AR(20), AR(30), AR(31), MA(4), MA(20), MA(30), MA(31) because this model have highest Adjusted R2, lowest AIC, lowest value of Sigma Square, highest number of significant coefficients and lowest value of S.E regression.

Table 1. Statistical Models for Meta Stock

ARIMA	AIC	Adjusted R^2	Sigma Square	Sig. Coefficient	S.E of Regression
AR(4), AR(20), AR(30), AR(31), MA(4), MA(20), MA(30), MA(31)	6.765889	0.062901	48.08735	5	7.004622
AR(4), AR(20), MA(30), MA(31)	6.772968	0.036268	49.85606	4	7.103467
AR(30), AR(31), MA(4), MA(20)	6.768638	0.040766	49.52336	5	7.086864
AR(4), AR(20), MA(4), MA(20),	6.796354	0.012522	51.0845	4	21.78758
AR(4), MA(4), MA(20), MA(30), MA(31)	6.769667	0.041861	49.46822	4	7.082821
AR(4), MA(20), MA(30), MA(31)	6.76927	0.040227	49.65127	5	7.088857
AR(4), MA(30), MA(31)	6.77715	0.029931	50.28506	4	7.126777
AR(4) MA(4)	6.80033	0.003664	51.75058	1	7.22262
AR(4) MA(20)	6.793195	0.011065	51.36615	2	7.195744
AR(4) MA(30)	6.785451	0.01937	50.9348	3	7.165467
AR(4) MA(31)	6.785071	0.019817	50.91156	3	7.163832
AR(20) MA(4)	6.79261	0.011651	51.33575	2	7.193614
AR(20) MA(20)	6.802262	0.001972	51.83849	1	7.228753
AR(20) MA(30)	6.784688	0.020571	50.8724	2	7.161077
AR(20) MA(31)	6.788572	0.016384	51.08987	2	7.176366
AR(30) MA(4)	6.785804	0.018906	50.95887	3	7.16716
AR(30) MA(20)	6.785705	0.019414	50.9353	2	7.165307
AR(30) MA(30)	6.79348	0.01152	51.34252	1	7.194089
AR(30) MA(31)	6.781798	0.02351	50.71976	3	7.150325
AR(31) MA(4)	6.785635	0.019117	50.94793	3	7.166391
AR(31) MA(20)	6.788554	0.016398	51.08918	2	7.176318
AR(31) MA(30)	6.781461	0.023877	50.70072	3	7.148983
AR(31) MA(31)	6.795422	0.0097377	51.45384	1	7.201883

Figure 6 shows the results of the selected models: AR (4), AR(20), AR(30), AR(31), MA(4), MA(20), MA(30), and MA (31) . Figure 7 shows the remaining dimensions. According to previous studies, for a model to be adequate, the residuals—defined as the difference among the authentic and forecast values—must consist of sequential errors consequently, the residuals of ARIMA of the proposed model exhibits white noise, indicating that the time series does not contain distinct additional noise components Thus the AR(P) and MA(Q) components have been optimized due to the increase of ACF and PACF respectively for lack of importance. Figure 8 shows that the probability of class residual correlations exceeding 5% indicates the absence of autocorrelation. Finally, Figure 9 displays that the likelihood estimate is greater than 5%, representing that the simulation is not heteroskedastic.

Dependent Variable: D(CLOSE)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 08/09/23 Time: 11:53
Sample: 7/20/2021 7/18/2023
Included observations: 502
Convergence achieved after 73 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.046246	0.363407	-0.127258	0.8988
AR(4)	-0.113605	0.100710	-1.128045	0.2599
AR(20)	-0.533417	0.117549	-4.537838	0.0000
AR(30)	0.272956	0.094919	2.875677	0.0042
AR(31)	-0.015072	0.101891	-0.147918	0.8825
MA(4)	0.010811	0.094875	0.113950	0.9093
MA(20)	0.637296	0.105304	6.051965	0.0000
MA(30)	-0.384777	0.079162	-4.860653	0.0000
MA(31)	0.138359	0.101719	1.360211	0.1744
SIGMASQ	48.08735	1.809269	26.57833	0.0000

R-squared	0.079735	Mean dependent var	-0.049602
Adjusted R-squared	0.062901	S.D. dependent var	7.235889
S.E. of regression	7.004622	Akaike info criterion	6.765889
Sum squared resid	24139.85	Schwarz criterion	6.849925
Log likelihood	-1688.238	Hannan-Quinn criter.	6.798859
F-statistic	4.736494	Durbin-Watson stat	1.972107
Prob(F-statistic)	0.000005		

Inverted AR Roots	.96+.18i	.96-.18i	.91	.88+.43i
	.88-.43i	.73+.54i	.73-.54i	.68+.71i
	.68-.71i	.47-.86i	.47+.86i	.28+.87i
	.28-.87i	.13+.97i	.13-.97i	.06
	-.13+.97i	-.13-.97i	-.29-.87i	-.29+.87i
	-.47-.86i	-.47+.86i	-.68-.71i	-.68+.71i
	-.74+.54i	-.74-.54i	-.88+.43i	-.88-.43i
	-.91	-.96+.18i	-.96-.18i	
Inverted MA Roots	.97-.17i	.97+.17i	.89	.89-.43i
	.89+.43i	.72-.55i	.72+.55i	.68+.71i
	.68-.71i	.47+.88i	.47-.88i	.36
	.26+.89i	.26-.89i	.12+.98i	.12-.98i
	-.14-.99i	-.14+.99i	-.31+.88i	-.31-.88i
	-.48+.87i	-.48-.87i	-.69-.72i	-.69+.72i
	-.77-.55i	-.77+.55i	-.90+.42i	-.90-.42i
	-.94	-.98-.18i	-.98+.18i	

Figure 6. ARIMA Model for Meta Platform Inc. closing stock prices after first difference.

The ARIMA model applied to Meta Inc. data, which includes AR terms at lags 4, 20, 30, and 31 and MA terms at the same lags, has been tested and found to produce white noise. Since this model fits the data well, we can confidently move forward to the forecasting phase.

Date: 08/09/23 Time: 12:17
Sample (adjusted): 7/20/2021 7/18/2023
Q-statistic probabilities adjusted for 8 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.013	0.013	0.0906	
		2	0.021	0.021	0.3243	
		3	-0.021	-0.021	0.5425	
		4	-0.002	-0.002	0.5454	
		5	-0.002	-0.001	0.5467	
		6	-0.006	-0.006	0.5642	
		7	0.013	0.013	0.6493	
		8	-0.024	-0.024	0.9503	
		9	0.050	0.050	2.2390	0.135
		10	0.049	0.049	3.4517	0.178
		11	0.035	0.030	4.0729	0.254
		12	0.038	0.037	4.8170	0.307
		13	0.030	0.030	5.2758	0.383
		14	0.015	0.014	5.3896	0.495
		15	-0.022	-0.020	5.6359	0.583
		16	-0.005	-0.005	5.6507	0.686
		17	0.044	0.048	6.6515	0.673
		18	-0.025	-0.027	6.9680	0.728
		19	-0.025	-0.031	7.2928	0.775
		20	0.033	0.032	7.8496	0.797
		21	0.027	0.021	8.2459	0.827
		22	-0.011	-0.021	8.3082	0.873
		23	-0.039	-0.047	9.1237	0.871
		24	0.007	0.005	9.1464	0.907
		25	0.014	0.018	9.2470	0.932
		26	0.034	0.026	9.8634	0.936
		27	0.011	0.007	9.9318	0.955
		28	-0.058	-0.055	11.728	0.925
		29	0.006	0.008	11.747	0.946
		30	-0.032	-0.034	12.297	0.951
		31	0.018	0.013	12.472	0.963
		32	-0.014	-0.006	12.575	0.973
		33	0.026	0.025	12.927	0.977
		34	-0.008	-0.011	12.963	0.984
		35	0.042	0.046	13.941	0.982
		36	0.012	0.011	14.017	0.987

Figure 7. Correlogram for Meta Platform Inc. residuals closing stock prices after first difference.

Date: 08/09/23 Time: 12:00
Sample (adjusted): 7/20/2021 7/18/2023
Included observations: 502 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.015	-0.015	0.1106	0.740
		2	0.007	0.007	0.1346	0.935
		3	-0.002	-0.002	0.1364	0.987
		4	0.001	0.001	0.1369	0.998
		5	-0.006	-0.006	0.1528	1.000
		6	0.006	0.006	0.1708	1.000
		7	-0.002	-0.002	0.1740	1.000
		8	-0.006	-0.006	0.1919	1.000
		9	0.011	0.011	0.2500	1.000
		10	0.013	0.013	0.3328	1.000
		11	-0.011	-0.010	0.3921	1.000
		12	0.012	0.012	0.4666	1.000
		13	-0.006	-0.006	0.4862	1.000
		14	0.015	0.015	0.6030	1.000
		15	-0.013	-0.012	0.6885	1.000
		16	-0.011	-0.012	0.7528	1.000
		17	-0.006	-0.005	0.7692	1.000
		18	-0.009	-0.010	0.8163	1.000
		19	-0.008	-0.009	0.8530	1.000
		20	0.027	0.027	1.2326	1.000
		21	0.012	0.013	1.3037	1.000
		22	-0.011	-0.011	1.3686	1.000
		23	-0.003	-0.004	1.3741	1.000
		24	-0.009	-0.010	1.4179	1.000
		25	-0.002	-0.001	1.4195	1.000
		26	-0.013	-0.013	1.5090	1.000
		27	0.012	0.012	1.5900	1.000
		28	-0.004	-0.003	1.5976	1.000
		29	-0.007	-0.008	1.6242	1.000
		30	0.003	0.002	1.6276	1.000
		31	0.004	0.004	1.6365	1.000
		32	-0.007	-0.007	1.6603	1.000
		33	-0.010	-0.011	1.7178	1.000
		34	-0.007	-0.008	1.7424	1.000
		35	-0.011	-0.011	1.8100	1.000
		36	-0.011	-0.010	1.8787	1.000

Figure 8. Correlogram for Meta Platform Inc. squared residuals closing stock prices after first difference.

In forecasting terms, the ideal model chosen is as follows.

$$P_t = c + \beta_1 P_{t-4} + \beta_2 P_{t-20} + \beta_3 P_{t-30} + \beta_4 P_{t-31} + \gamma_1 E_{t-4} + \gamma_2 E_{t-20} + \gamma_3 E_{t-30} + \gamma_4 E_{(t-31)} + \varepsilon \quad \text{(eq-1)}$$

Heteroskedasticity Test: ARCH

F-statistic	0.109268	Prob. F(1,499)	0.7411
Obs*R-squared	0.109682	Prob. Chi-Square(1)	0.7405

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 08/09/23 Time: 12:28
Sample (adjusted): 7/21/2021 7/18/2023
Included observations: 501 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	48.85440	13.06020	3.740709	0.0002
RESID^2(-1)	-0.014796	0.044762	-0.330556	0.7411

R-squared	0.000219	Mean dependent var	48.14163
Adjusted R-squared	-0.001785	S.D. dependent var	288.0581
S.E. of regression	288.3150	Akaike info criterion	14.16997
Sum squared resid	41479658	Schwarz criterion	14.18680
Log likelihood	-3547.577	Hannan-Quinn criter.	14.17657
F-statistic	0.109268	Durbin-Watson stat	1.999775
Prob(F-statistic)	0.741118		

Figure 9. Heteroskedasticity test for Meta Platform Inc.

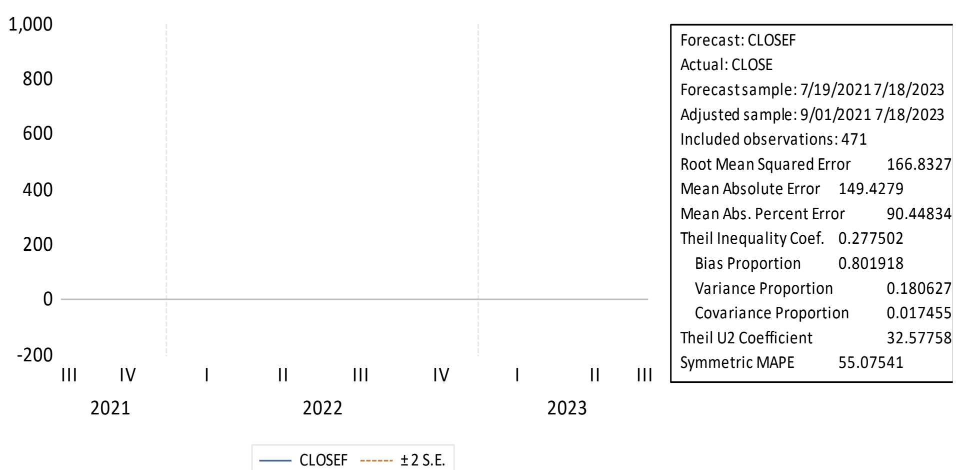

Figure 10. actual and forecasted values graph for Meta Platform Inc.

Figure 11. actual and forecasted values graph for Meta Platform Inc.

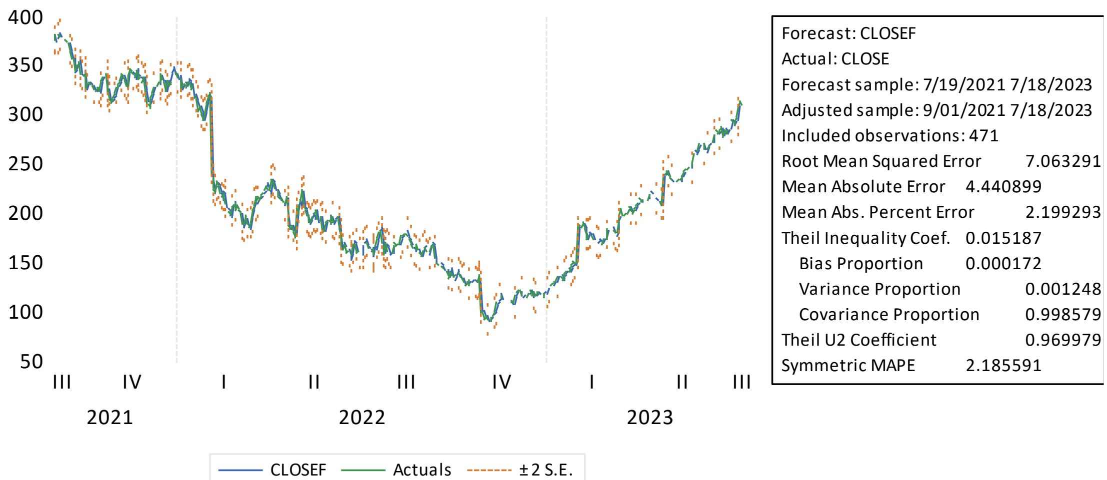

Figure 12. actual and forecasted values graph for Meta Platform Inc.

Figures 10 and 12 reveal a remarkable agreement between the predicted values and the model values, which shows the accuracy of the model's predictive ability The root mean square error (RMSE) is a remarkable 166.8327 for active forecast, 7.063291 which is even more impressive for static consider. These exceptionally low errors demonstrate a high fit of the model, highlighting its effectiveness in capturing underlying patterns in the data. Furthermore, the mean absolute error (MAE) of the difference between the actual and predicted values is almost negligible—149.4279 for the dynamic prediction, it registers only 4.4408 for the positive prediction the static This difference is close to the accuracy of the zero model It also further demonstrates its reliability and shows a clear picture of its ability to make predictions that do not deviate significantly from reality.

CONCLUSION AND POLICY IMPLICATION

Conclusion

Forecasting is the art and science of predicting the future, a particularly challenging skill when practiced in a world of constantly changing stock prices The challenge lies in the inherent complexity of stock markets, a field whose volatility it is marked by unpredictability and uncertainty of outcome. Forecasting stock prices is not just a technical feat but a puzzle that requires keen insight, sophisticated tools, and nuanced understanding of market dynamics.

Capital markets are not just places of business; They are the lifeblood of economic growth. According to Ali et al., (2022), the health of a country's stocks market often reflects the strength of the wider economy. U.S. a capital market with a staggering $46.2 trillion in assets (total US stock market value | Siblis Research) is a testament to its enormous impact on national and global economies.

In such a large and dynamic market, so many investors, both experienced and novice, are always looking for exhibits. They understand that the key to successful investing lies in the ability to anticipate market trends and manage risk. Stock market volatility is both a challenge and an opportunity, and accurate forecasting is not only a valuable tool, but also a necessity. Since investors use these forecasts to guide their decision making, weigh risks, and opportunities, the importance of accurate and reliable forecasts are becoming increasingly important as market developments can change their fortunes in an instant. It enables investors to confidently navigate the complexities of the market, allowing them to make informed decisions in a surprisingly fluid environment. This article rationalizes how to apply the ARIMA model to build a thorough stocks value projection platform for Meta Stocks. In this paper we used the data of Meta Platforms Inc.'s daily closing stock price time series data ranges from July 19, 2021, to July 18, 2023, given dataset has total 503 observations. The source of the data was Yahoo Finance.

The ARIMA model applied to Meta Inc. data, which includes AR terms at lags 4, 20, 30, and 31 and MA terms at the same lags, has been evaluated and found to produce white noise since it fits the data. The existing ending prices of the stocks of Meta Platforms Inc. depend on the previous shocks of 4, 20, 30, and 31 days and the mean precariousness of the existing price of stock depends on the volatility in preceding 4, 20, 30, and 31 days. The adjusted R2 explains the price change between the prior period and the present for Meta Stocks.

Policy Implications

The study shows how well the ARIMA model predicts stock prices, especially Meta Platforms Inc. Because this insight can be used by managers and investors to help make better investment choices. Financial managers can optimize investments and reduce exposure to risk by understanding how past market shocks have affected current pricing and strategies for anticipating future growth. Analysis of stock price volatility over days (4, 20, 30, 31) provides insightful information for risk management. Using this information, managers can more accurately forecast and prepare for potential market

fluctuations, enabling them to implement more successful risk mitigation strategies. It can be especially helpful for trading near-term planning or changing long-term budgetary conditions in anticipated markets. The study opens the door for further research, encouraging managers to examine other sectors and economic variables in their forecasting models. This forward-looking approach can help businesses stay ahead of market trends, ensuring long-term success and competitiveness.

Limitations and future recommendations

This study will be crucial in guiding future research by incorporating new industries, economic and financial variables, and placing a stronger emphasis on sensitivity analysis and forecasting techniques. Although the ARIMA model has proven to work well for Meta Platforms Inc., its application may be limited when dealing with companies or other industries that exhibit different market dynamics. Managers should exercise caution when extrapolating the results of this study to other settings, which are no longer validated. The analysis is based on closing daily stock prices from a typical two-year period. This limited data may not fully capture broader market trends or account for long-term factors affecting stock prices. Managers should consider adding additional data sources to these models to increase the robustness of the forecasts. The unpredictability and volatility of the stock market is also a major challenge for the accuracy of the ARIMA model in this study unexpected events, such as economic shocks or geopolitical crises, can still trigger their withdrawal significantly deviated from the predicted results, limiting the reliability of the model in some cases. Future studies can be conducted to develop a reliable prediction model that will validate the research findings produced by the ARIMA model.

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